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Partitioning the Impacts of Streamflow and Evaporation Uncertainty on the Operations of Multipurpose Reservoirs in Arid Regions

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ABSTRACT

Undergoing changes in global climate are expected to alter the hydrologic regime of many river basins worldwide, expanding historically observed variability as well as increasing frequency and intensity of extreme events. Understanding the vulnerabilities of water systems under such uncertain and variable hydrologic conditions is key to support strategic planning and design adaptation options. In this paper, we contribute a multi-objective assessment of the impacts of hydrologic uncertainty on the operations of multipurpose water reservoirs systems in arid climates. We focus our analysis on the Dez and Karoun river system in Iran, which is responsible for the production of more than 20% of the total hydropower generation of the country. A system of dams controls most of the water flowing to the lower part of the basin, where irrigation and domestic supply are strategic objectives, along with flood protection. We first design the optimal operations of the system using observed inflows and evaporation rates. Then, we simulate the resulting solutions over different ensembles of stochastic hydrology to partition the impacts of streamflow's and evaporation's uncertainty. Numerical results show that system operations are extremely sensitive to alterations of both the uncertainty sources. In particular, we show that in this arid river basin long-term ob-

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jectives are mainly vulnerable to inflows uncertainty, while evaporation rates' uncertainty mostly impact on short-term objectives. Our results suggest that local water authorities should properly characterize hydrologic uncertainty in the design of future operations of the expanded network of reservoirs, possibly investing also in the improvement of the existing monitoring network to obtain more reliable data for modeling streamflow and evaporation processes.

INTRODUCTION

There is growing scientific consensus on the ongoing alteration of historical hydrologic regimes in many regions of the world (Battisti and Naylor 2009). These changes are expected to severely affect future freshwater availability and health of water dependent systems (van Vliet et al. 2013; Haddeland et al. 2014). Better understanding the main vulnerabilities of water systems under future climate conditions is key to mitigate potentially negative impacts and explore adaptation options. Most of climate change assessment studies rely on global climate projections (Christensen and Christensen 2007; Giuliani et al. 2016; Turner et al. 2017) according to a scenario-led approach, where impacts are estimated through a top-down approach relying on a cascade of models (Wilby and Dessai 2010). Projections of greenhouse gas emission scenarios or representative concentration pathways (IPCC 2013) are used to drive the simulation of global climate models, whose outputs are then downscaled and used as inputs in a hydrological model to obtain future streamflow projections. However, the discrete nature of these projections challenges the use of top-down approaches for decision-making purposes and, indeed, most research studies stop at the impact assessment stage (Brown et al. 2012).

To better characterize the risks in the operations of water systems associated to the increasing variability of the hydrological cycle, recent works have shifted from scenario-led to scenario-neutral approaches, which determine the vulnerability of the system when exposed to a wide range of plausible uncertain scenarios, whose probabilities are not known or widely agreed on (Lempert 2002; Brown et al. 2012; Herman et al. 2015; Kwakkel et al. 2016). Several studies have assessed the vulnerability of water reservoirs operations by using synthetically generated scenarios (Whateley et al. 2014; Culley et al. 2016). Generally, these preserve the observed spatiotemporal correlation structure of the generated variables (e.g., temperature, precipitation, or streamflow) and, at the same time, extend beyond the historical record to discover situations in which existing or planned strategies may fail to meet minimum performance levels (Herman et al. 2016). This scenario-neutral strategy hence allows considering in the analysis different sources of uncertainty, including both hydrological and climate variability, to produce insights about how to adapt water systems operations to future climate extremes (Forzieri et al. 2014).

Yet, assessing the impacts of inflows' uncertainty on water reservoir operations represents only one part of the equation. In fact, an alteration of the hydrologic regime does not impact solely on the inflow pattern, but often implies a modification of the air temperature, which is projected to significantly increase over the next years (Lobell et al. 2011). In particular, growing temperature will produce increasing evaporation rates, altering reservoir's storage dynamics by increasing evaporation losses. Although some works developed detailed analyses on evaporation rates and their relationships with temperature and other hydrologic variables (Xu and Singh 2001; Rosenberry et al. 2007; Hooshmand et al. 2013; Gorjizade et al. 2014), the focus of these studies is generally on hydrological modeling for improving the representation of the natural water processes in a river basin. The impacts of evaporation rates' uncertainty on the operations of water systems are still largely unexplored. In a number of water systems, particularly in arid and semi-arid regions where evaporation losses are key components of the hydrologic balance (Block and Strzepek 2010; Beck and Bernauer 2011; Giuliani and Castelletti 2013), these impacts are very likely to be comparable or even larger than streamflow uncertainty. High evaporation may contribute in drawing down reservoirs' levels, negatively affecting several water-related sectors such as hydropower production and water supply. At the same time, low evaporation may result in excessively high water storages, which increase the frequency of spillages and the risk of floods.

In this paper, we contribute a multi-objective assessment procedure for partitioning the impacts of streamflow and evaporation uncertainty on the operations of multipurpose reservoirs in arid river basins. The analysis aims at quantifying how the performance of operating policies designed over historical hydrologic conditions may degrade when evaluated over stochastic ensembles of streamflow and evaporation. In particular, we focus on the role of stochastic hydrology without imposing any climate trend. As a consequence, the estimated impacts of stochastic hydrology represent a lower bound of the possible performance degradation that can be expected if the system is exposed to a wide range of plausible uncertain scenarios.

The Dez and Karoun rivers system in Iran is used as study site. In this river basin, the multipurpose operations of Dez, Karoun 1, and Masjed Soleyman reservoirs account for 20% of the national hydropower capacity and control most of the water flowing to the downstream part of the system, where irrigation and domestic supply, especially to the city of Ahwaz, are also strategic objectives. In addition, the existing energy-driven regulation of these reservoirs is producing frequent flood inundation along the Karoun river, downstream of Masjed Soleyman dam. Seasonal low precipitations, high evaporation rates, and severe drought risks make the role of water reservoirs and their operations crucial in balancing these competing water demands in the system.

In fact, water resources in Iran have recently experienced increasing pressures from rising demands (Yazdandoost 2016; Madani et al. 2016), which induce overexploitation of available resources (AghaKouchak et al. 2015a), and recurrent droughts (Golian et al. 2015), which negatively impact primarily on agriculture, representing 10-20% of the national economic volume (Khorami and Pierof 2013), and also on urban water supply and ecosystem services (Salami et al. 2009; Bari Abarghouei et al. 2011). The situation is particularly severe in arid and semiarid regions, such as in the case of Khouzestan province, where the average discharge in the last decade of Karkheh, Karun, and Marun rivers is decreased with respect to the historical record of 49%, 37% and 40%, respectively (Musavi 2005), or in the case of Lake Urmia drying up (AghaKouchak et al. 2015b; Hesami and Amini 2016). Combining undergoing large investments in infrastructure (e.g., construction of new dams) with non-structural options, such as improved water reservoir operations (Biemans et al. 2011), international water transfer (Gohari et al. 2013), or water markets (Hollinshead and Lund 2006), becomes key for securing sustainable water resources over the next years (Madani 2014).

The goal of our analysis is partitioning the role of streamflow and evaporation rates uncertainties and quantifying their independent as well as combined influence on operating objectives with different time dynamics, including both short-term objectives characterized by fast dynamics (e.g., hydropower production and flood control) and long-term objectives evolving over longer time scales (e.g., water supply). Specifically, we first design the optimal operations of the three reservoirs under observed hydrologic conditions via evolutionary multi-objective direct policy search (EMODPS) (Giuliani et al. 2016), an approximate dynamic programming approach that combines direct policy search, nonlinear approximating networks, and multi-objective evolutionary algorithms. The advantage of using EMODPS is the possibility of estimating an approximation of the Pareto front in a single run of the algorithm, which supports the exploration of the multi-dimensional tradeoffs between the conflicting objectives. The resulting Pareto approximate solutions are then re-evaluated via Monte Carlo simulation over different ensembles of stochastic hydrologic conditions, including synthetic inflows, synthetic evaporation rates, and a combination thereof. Quantifying the variability of the policy performance, especially the possible degradation of performance, across different objectives over the three generated ensembles allows unpacking the impacts of inflows' and evaporation' uncertainty and, therefore, partitioning the associated vulnerabilities in the system operations.

The rest of the paper is organized as follows: the next section introduces the Dez and Karoun rivers study site, followed by the description of the methodologies adopted for the design of the multipurpose reservoirs operations and for the synthetic generation of ensembles of inflows and evaporation rates. Numerical results are then reported, while final remarks, along with issues for further research, are presented in the last section.

STUDY SITE

Iran is the second largest country in Middle East and is characterized by a very low per capita freshwater availability, estimated in around 2000 m^3/year against a world average of 5800 m^3/year (Yang et al. 2003), with a projected 25% decrease by 2030 due to the population growth. The country has a broad spectrum of climatic conditions across regions: the average annual precipitation is 250 mm per year, with 75% of it falling out of the irrigation season. Precipitation is also extremely diverse across regions, ranging from 1000 mm/year in the northern provinces to 50 mm/year in the central part of the country. The temperature pattern is highly variable too, ranging from -20°C in the northwest to 50°C along the Persian Gulf. In such climatic conditions, where around 65% of the country is considered to be arid, a key role in the annual water balance is represented by evaporation losses, which account for up to 40% of the total volume of water stored in Iranian reservoirs (Gorjizade et al. 2014).

The Karoun and Dez rivers basin

The Karoun River (Figure 1a) is the largest river by discharge in Iran. It rises in the Zard Kuh mountains and flows for 950 kilometers before reaching the Persian Gulf. The river has an average discharge of 575 m^3/s and its catchment covers an area of 65,230 km^2. Dez River is the largest tributary of Karoun. It is around 400 kilometers long and joins Karoun River 40 kilometers north of the city of Ahvaz (Capital of Khuzestan Province), forming the so-called Great Karoun. This latter flows through Ahvaz and reaches the Persian Gulf about 120 km south of Ahvaz. The Great Karoun is the only navigable river of the country and is an important route for transportation of petroleum to the Persian Gulf.

The basin is characterized by two seasons: rainy season between October and May, which covers 96% of the rainfall, and dry season from June to September. The average annual amount of rainfall over the catchment can be estimated in approximately 500-600 mm per year. Temperature varies from an extremely hot summer characterized by air temperature around 54°C to mild winter with sub-zero temperature for most areas of the region. The annual pan evaporation varies between 1500 to 2200 mm (Hooshmand et al. 2013). Dez and Karoun rivers carry more than 20% of the surface water supply of the whole country (Karamouz et al. 2005). Due to the low quality of groundwater in this catchment, Karoun and Dez rivers are the main water suppliers for agricultural and agro-industrial uses, providing water for irrigation to over 300,000 hectares of the surrounding plain. Beside irrigation, domestic water supply is another main sectors served by these rivers. The total water demand from Dez and Karoun rivers is estimated to be larger than 9000×10^6 m^3, with 28% allocated to downstream of Karoun 1 dam, 45% is allocated downstream of Dez dam, and the rest downstream of their confluence point, Bande-Ghir (Karamouz et al. 2000).

In order to cope with these demands, several dams have been constructed or are under construction on Karoun river and its tributaries (Dariane and Momtahen 2009). In the current study, Karoun 1, Masjed Soleyman, and Dez dams are investigated as three strategical dams constructed on Dez and Karoun rivers, which control most of the water flowing to the downstream part of the system and account for more than 20% of national hydropower generation. The main characteristics of these reservoirs are summarized in Table 1. The operations of these reservoirs is becoming critical for balancing the competing demands in the system. Yet, the extremely high evaporation losses represent a major challenge for water operators in the region, with additional difficulties due to the large uncertainties affecting the evaporation process and its impacts on the reservoirs' dynamics. According to a report released by Water Authorities in Iran in 2006, the annual evaporation volume of four of these major dams (namely Shahid Abbaspour (Karoun 1), Dez, Karoun 3, and 4) is about 4.2×10^6 m^3, which is much greater than the volume of water stored in Masjed Soleyman dam.

In this work, we use a 3-years evaluation horizon, from April 2003 to March 2006, for which observed trajectories of inflows and evaporation rates are available. We then generate different ensembles of stochastic hydrologic conditions as described in the next section.

METHODS AND TOOLS

Our multi-objective assessment procedure is composed of four main building blocks: (*i*) modeling the system and formalization of multiple objective functions; (*ii*) design of Pareto optimal (or approximate) operating policies exploring the system tradeoffs; (*iii*) generation of stochastic hydrologic conditions; (*iv*) Monte Carlo simulation of the solutions obtained at point (ii) over the stochastic ensembles generated at point (iii).

Model and objectives

The model of the Dez and Karoun system (Figure 1b) is mainly based on the dynamics of the three water reservoirs and is defined by the mass balance equations of the water volume stored in each reservoir, with a decision time step of 24 hours:

$$s^D_{t+1} = s^D_t + n^D_{t+1} - r^D_{t+1} - E^D_{t+1} \tag{1a}$$

$$s^K_{t+1} = s^K_t + n^K_{t+1} - r^K_{t+1} - E^K_{t+1} \tag{1b}$$

$$s^{MS}_{t+1} = s^{MS}_t + r^K_{t+1} - r^{MS}_{t+1} - E^{MS}_{t+1} \tag{1c}$$

where s^i_t (i= D, K, MS) is the storage of the reservoirs at time t, while n^i_{t+1} , r^i_{t+1} and E^i_{t+1} are the reservoirs' inflow, releases, and evaporation losses, respectively, between t and $t+1$. In the adopted notation, the time subscript of a variable indicates the instant when its value is deterministically known. The reservoir storage is measured at time t, whereas, for example, the inflow has subscript $t+1$, denoting the water volumes entering into the reservoir in the time interval $[t, t+1)$. The released volume is a nonlinear function of storage, inflow, evaporation losses, and the release decisions u^i_t at each time step, which accounts for any possible deviation of the actual release r^i_{t+1} from the decision u^i_t due to unintentional spills or any other physical legal constraint (Piccardi and Soncini-Sessa 1991).

To maximize the performance of the overall system, in this work we adopt a centralized point of view and fully coordinated operations of the three reservoirs as the owner and operator of all the dams is the Iran Water and Power Resources Development Company. The four operating objectives, representing hydropower production, water supply to the agricultural districts downstream of Dez dam and to the city of Ahvaz, and flood protection downstream of Masjed Soleyman dam, are formulated as follows:

- *Hydropower production*: daily average energy production in the system, defined as the sum of productions of the three powerplants (to be maximized).

$$J^{Hyd} = \frac{1}{H} \sum_{i=1}^{3} \sum_{t=0}^{H-1} \eta^i g \gamma_w \Delta_{t+1}^i q_{t+1}^{turb,i} 10^{-6} \tag{2}$$

  where i=(D, K, MS), η^i is the turbine efficiency, $g = 9.81$ m/s^2 is the gravitational constant, $\gamma_w = 1000$ (kg/m^3) is the water density, Δ_{t+1}^i is the hydraulic head (*i.e.*, reservoir level minus the tail water level), $q_{t+1}^{turb,i}(m^3/s)$ is the turbined flow, and H is the evaluation horizon.

- *Water supply to agricultural districts*: daily average squared water deficit, defined as the squared positive difference between the water demand of the irrigated areas downstream of Dez dam (Figure 2) and the water supplied (to be minimized).

$$J^{Irr} = \frac{1}{H} \sum_{t=0}^{H-1} max((w_t^{Irr} - q_{t+1}^{Irr}), 0)^2 \tag{3}$$

  where w_t^{Irr} is water demand of irrigated areas in each time step and q_{t+1}^{Irr} is water diverted from Dez river and used for irrigation.

- *Water supply to Ahvaz city*: daily average squared water deficit in Ahvaz, defined as the squared positive difference between the urban water demand (Figure 2) and water supplied to the city (to be minimized).

$$J^{A} = \frac{1}{H} \sum_{t=0}^{H-1} max((w_t^{A} - q_{t+1}^{A}), 0)^2 \tag{4}$$

where w_t^A is water demand of Ahvaz at each time step and q_{t+1}^A is the water supplied to the city. This amount of water is defined as the sum of water released from Masjed Soleyman dam and the flow in the Dez river downstream of the irrigation diversion.

- *Flooding*: Maximum flooded area downstream of Masjed Soleyman dam, defined according to Heidari (2009) as a function of the water released from the dam:

$$J^{Flood} = \max_{t=0,\dots,H-1} \left(\frac{r_{t+1}^{MS}}{0.2047} \right)^{1/0.9793} \tag{5}$$

Operating Policy Design

The optimal operations of the Karoun and Dez rivers system is designed via evolutionary multi objective direct policy search (EMODPS, see Giuliani et al. (2016)). EMODPS is an approximate dynamic programming method, which relies on a simulation-based optimization approach combining direct policy search, nonlinear approximating networks, and multi-objective evolutionary optimization to discover Pareto approximate operating policies for multi-purpose reservoir systems. The key components of EMODPS are (*i*) the direct search of solutions in the policy space, where the candidate operating policies are defined by using flexible non-linear approximating networks, and (*ii*) the use of multi-objective evolutionary algorithms to identify those policy parameterizations that yield Pareto approximate reservoir operating policies.

Direct policy search (DPS, see (Sutton et al. 2000; Rosenstein and Barto 2001)), also known as parameterization-simulation-optimization in the water resources literature (Koutsoyiannis and Economou 2003), is a simulation-based approach where the operating policy is first parameterized within a given family of functions and, then, the policy parameters are optimized with respect to the operating objectives of the problem. In this work, we use Gaussian radial basis functions (RBFs) to parameterize the operating policy as they are capable of representing functions for a large class of problems (Busoniu et al. 2011) and have been demonstrated to be effective in solving multi-objective policy design problems (Giuliani et al. 2014; Giuliani et al. 2017). In complex many-objective problems, namely when the number of objectives grows to three or more (Fleming et al. 2005), a priori knowledge can be counterproductive as it might restrict the search for the optimal policy to a subspace of the decision space that might not include the optimal solution. The adoption of universal approximators, such as artificial neural networks or basis functions (Tikk et al. 2003), partially overcomes this limitation by providing flexibility to the shape of the operating rule.

In this formulation, the k-th release decision in the vector $\mathbf{u}_t$ (with k =D,K,MS) is defined as:

$$u_t^k = \sum_{i=1}^{N} w_{i,k}\varphi_i(\mathcal{I}_t) \tag{6}$$

where N is the number of RBFs $\varphi(\cdot)$ and $w_{i,k}$ is the weight of the i-th RBF. The weights are formulated such that they sum to one (i.e., $\sum_{i=1}^{n} w_{i,k} = 1$) and are non-negative (i.e., $w_{i,k} \geq 0 \quad \forall i$). The single RBF is defined as follows:

$$\varphi_i(\mathcal{I}_t) = \exp\left[-\sum_{j=1}^{M} \frac{((\mathcal{I}_t)_j - c_{j,i})^2}{b_{j,i}^2}\right] \tag{7}$$

where M is the number of input variables ($\mathcal{I}_t$) and $\mathbf{c}_i, \mathbf{b}_i$ are the M-dimensional center and radius vectors of the i-th RBF, respectively. The parameter vector $\boldsymbol{\theta}$ is therefore defined as $\boldsymbol{\theta} = [(c_1, \ldots, c_M), (b_1, \ldots, b_M), (w_1, \ldots, w_n)]_1^N$. The total number of policy parameters is therefore equal to $N(2M + K)$.

The optimal values of the policy parameters $\boldsymbol{\theta}^*$ are determined by solving the following optimization problem:

$$\boldsymbol{\theta}^* = \arg\min_{\boldsymbol{\theta}} \mathbf{J}(\boldsymbol{\theta}) \tag{8}$$

where the decision variables are the policy parameters $\boldsymbol{\theta} \in \Theta$, the objective functions are the operating objectives $\mathbf{J}$ defined in eqs. 2-5, which are obtained by simulating the system under the policy $p_\theta = \{\mu(\mathcal{I}_t, \theta); t = 0, ..., H - 1\}$, and the problem is constrained by the dynamics of the system (eq. 1).

In this work, we use the self-adaptive Borg MOEA (Hadka and Reed 2013) for optimizing the policy parameters as it has been shown to be highly robust in solving multi-objective optimal control problems, where it met or exceeded the performance of other state-of-the-art MOEAs (Zatarain-Salazar et al. 2016). This algorithm employs multiple search operators that are adaptively selected during the optimization based on their demonstrated probability of generating quality solutions. In addition, it assimilates several other recent advances in the field of MOEAs, including an ε-dominance archiving with internal algorithmic operators to detect search stagnation, and randomized restarts to escape local optima.

Stochastic Hydrology Generation

The major drawback of the EMODPS method is related to the simulation-based optimization of the policy parameters, where the deterministic use of observed historical records to evaluate a candidate operating policy can strongly underestimate the impacts of hydrologic variability and extremes (Cui and Kuczera 2005). To evaluate how hydrologic uncertainties impact the reliability of the designed policies, in this study we generated a stochastic ensemble of realizations of streamflow and evaporation rates for the Karoun and Dez rivers system.

Streamflow generation

A large number of methods for synthetic streamflow generation has been proposed in the literature (Box and Jenkins 1970; Lall and Sharma 1996; Yates et al. 2003). According to Rajagopalan et al. (2010), these methods can be classified as parametric approaches, which fit a standard functional form for the observed data, and nonparametric approaches, which instead define empirical distributions. In this study, the nonparametric K-Nearest Neighbor resampling method proposed by Nowak et al. (2010) is used to generate the ensemble of inflow trajectories. This data-driven method captures the observed statistics, is consistent with the lag correlation structures in the observed data, and ensures summabililty and continuity across the daily time scale.

The KNN resampling procedure is based on the generation of temporally and spatially cumulated annual data and their disaggregation into daily and spatially distributed flow values. The synthetic annual data Z are generated by means of an auto-regressive model calibrated over the historical time series. In our case, an autoregressive model of order 0 (i.e., Z is sampled from a normal probability distribution function with no autocorrelation) has been used as the limited length of the historical time series (i.e., three years) doesn't allow a robust estimate of the annual flow autocorrelation. The historical data are then used to compute the proportion matrix P_t^j, which contains the proportion of the annual data occurring in each day t of the year and each site j. Then, K nearest neighbors of the generated annual value Z are identified from the historical records, with $K = \sqrt{N_y}$ being N_y the number of years in the historical time series. A weight is assigned to each of the K-nearest neighbors as follows:

$$W(i) = \frac{\left({}^{1}/_{i}\right)}{\left(\sum_{i=1}^{K} {}^{1}/_{i}\right)} \tag{9}$$

where i is the neighbor index, with $i = 1$ identifying the nearest neighbor. According to the probabilities defined by their weights, one of the K-nearest neighbors is randomly selected. Finally, the proportion matrix of the selected year $P_t^j(y)$ is used to disaggregate the annual flow Z to obtain daily data for each site $d_t^j = Z \cdot P_t^j(y)$. The procedure is iterated to generate an ensemble of daily streamflows for each Z, and then repeated for multiple synthetic annual data.

Figure 3 illustrates the annual flow duration curve of the historical inflows of the Dez and Karoun rivers system (black lines) and the synthetically generated 50-members ensemble (gray lines). Each ensemble member corresponds to a 3-years trajectory of daily streamflow in the two rivers. It is worth noting that the generated ensemble expands the observed variability in terms of both high and low flow conditions, thus representing a suitable means for exploring the vulnerabilities of history-based operating policies.

Evaporation generation

Beside the KNN streamflow ensemble, to assess the role of evaporation rates' uncertainties on the system's operations we also generated an ensemble of evaporation rates for the three modeled reservoirs (i.e., Dez, Karoun 1, Masjed Soleyman). A number of models (Thornthwaite 1948; McGuinness and Bordne 1972; Blaney and Criddle 1950; Kharrufa 1985) have been tested to describe the evaporation as a function of the temperature and other hydrologic variables. None of these models reproduces accurately the observed values in the considered study site, as reported in Table 2. In addition, the values of annual evaporation reported in the literature for this system are also extremely variable (see Table 2).

Given this large uncertainty, we use a resampling approach also here and we generate the ensemble of evaporation scenarios by sampling an annual value Z^e according to a uniform probability distribution $F(Z^e)$, i.e.

$$F(Z^e) = \begin{cases} \frac{1}{b-a} & \text{for } a \le Z^e \le b \\ 0 & \text{for } Z^e < a \text{ or } Z^e > b \end{cases} \tag{10}$$

where the ranges $[a, b]$ are identified from the values reported in the literature.

Then, similarly to the K-Nearest Neighbor resampling method adopted for the streamflow generation (see the previous section), we disaggregate every generated annual evaporation value Z^e into monthly evaporation Z^e_m, using the monthly proportion matrix P^e estimated from the observed evaporation data, i.e. $Z^e_m = Z^e \cdot P^e$.

Figure 4 shows the 50 evaporation scenarios for the three reservoirs, with the black line representing the observed monthly average evaporation (Ghorbani et al. 2009) and the gray lines representing the generated evaporation values. As in the case of the streamflow ensemble, the generated evaporation rates show a large variability around the observed values, thus representing a suitable means for assessing the vulnerabilities of the system operations.

Experiment Setting

The operating policy of Dez, Karoun 1, and Masjed Soleyman reservoirs is parameterized using 9 RBFs, accounting for 117 parameters (i.e., decision variables). This parameterized policy provides the release decisions for the three reservoirs as a function of the following set of variables: $\mathcal{I}_t = [sin(2\pi t/365), cos(2\pi t/365), h_t^K, h_t^{MS}, h_t^D]$. Beside the water levels in the three reservoirs, representing the current water available, the time is included among the policy inputs to take into account the time-dependency and cyclostationarity of the system and, consequently, of the operating policy.

The adopted EMODPS method relies on the Borg MOEA. Since the algorithm has been shown to be relatively insensitive to the choice of the algorithm parameters, we used the default algorithm parameterization as suggested by Hadka and Reed (2013), with epsilon dominance values set equal to 500 kWh/day for Hydropower production, 80 km^2 for Flooding, 100 (m^3/s)^2 for Irrigation, and 100 (m^3/s)^2 for Ahwaz water deficit. Each optimization was run for 100,000 function evaluations. The analysis of runtime progress of the optimization (Biglarbeigi 2014) ensures the attainment of high fidelity approximations of the Pareto approximate set with this number of function evaluations. To improve solution diversity and avoid dependence on randomness, we run 20 independent optimization trials. The final set of Pareto approximate policies for each experiment is defined as the set of non-dominated solutions from the results of all the optimization trials.

The design of the history-based Pareto approximate operating policies is performed over a 3-years evaluation horizon, from April 2003 to March 2006, using the observed trajectories of inflows and evaporation rates. Then, to partition the uncertainty associated to streamflow and evaporation rates, we performed the following four experiments:

- *Historical evaluation*: the performance of the designed operating policies is evaluated over the same 3 hydrologic years used for the optimization, namely from April 2003 to March 2006, using historical trajectories of inflows and evaporation rates;
- *Ensemble of streamflow*: the performance of the designed operating policies is re-

evaluated via Monte Carlo simulation over 50 scenarios of synthetically generated streamflows and the historical evaporation rates;

- *Ensemble of evaporations*: the performance of the designed operating policies is re-evaluated via Monte Carlo simulation over 50 scenarios of synthetically generated evaporation rates and the historical inflows trajectories;
- *Mixed Ensemble*: the performance of the designed operating policies is re-evaluated via Monte Carlo simulation over 50 scenarios of synthetically generated scenarios, constructed by randomly sampling 50 generated ensembles of inflows and evaporation rates from the corresponding ensembles.

RESULTS

Policy performance over history

Figure 5 reports the performance of the Pareto approximate operating policies evaluated over the historical period from April 2003 to March 2006, using the observed values of inflows and evaporation rates. In the figure, the water supply to the agricultural districts (J^{Irr}) and the water supply to Ahwaz city (J^{A}) are plotted on the primary axes. The black arrows identify the directions of increasing preference, with the bottom-left corner of the figure representing the ideal point with respect to these two objectives. The dimension of the circles is proportional to the maximum flooded area downstream of Masjed Soleyman dam (J^{Flood}), with the best solutions represented by the smallest circles. Finally, the daily average hydropower production (J^{Hyd}) is represented by the light/dark gray color ramp, corresponding to the minimum and maximum production, respectively. So in the figure, the ideal solution of the 4-objective policy design problem is a small and dark circle close to the bottom-left corner of the figure.

The results reported in Figure 5 show clear tradeoffs between the four considered operating objectives. The solution that provides the highest hydropower production (PH), represented by a black circle in the upper right part of the solutions' set, has a poor performance in both irrigation and Ahvaz water supply objectives, even though it does not produce extremely large flooded area. However, given the strategic role of hydropower production in this system within the Iranian energy sector, there are relevant concerns associated to the impacts of this solution on the water supply sector.

The optimal flood control is obtained with solution PF, which produces the smallest flooded area by sacrificing some hydropower production and also attaining a medium-low performance in terms of water supply to Ahvaz. Conversely, this solution is quite good in terms of water supply for agriculture as floods are produced by Masjed Soleyman releases, while the irrigated areas withdraw water from Dez River.

Finally, the figure shows a strong conflict between supplying water for irrigation, with the minimum water deficit attained by the policy denoted as PI, and for Ahvaz city, with the minimum water deficit attained by policy PA. These two solutions are indeed the two extremes of the tradeoff curve between J^{Irr} and J^{A}. In fact, the optimal operations of the system for these two objectives require a different allocation of the water available during the year due to the mismatch in the associated water demands' pattern for irrigation and urban uses (see Figure 2).

Overall, the set of Pareto approximate operating policies illustrated in Figure 5 provides a rich context for understanding the complex management tradeoffs and dynamics in the Dez and Karoun rivers system and has the potential for supporting stakeholders' negotiation in order to facilitate the identification of candidate compromise solutions. However, these results might overestimate the system's performance in meeting the competing objectives as the evaluation is performed over deterministic historical inflows and evaporation rates, thus overlooking the impacts of hydrologic uncertainty.

Policy Performance over stochastic hydrology

To evaluate policy vulnerabilities with respect to hydrologic uncertainty, we re-evaluate all the solutions illustrated in Figure 5 via simulation over three different ensembles of stochastic hydrologic conditions including (i) stochastic inflows realizations and historical evaporation rates; (ii) historical inflows and stochastic evaporation rates realizations; and

(iii) mixed ensembles combining stochastic inflows and stochastic evaporation rates.

Figure 6 provides a synthesis of the outputs of the 12,900 simulations performed (86 history-based Pareto approximate alternatives times 3 ensembles times 50 realizations for each ensemble) by quantifying the performance uncertainty of the four single-objectives optimal solutions (PH, PF, PI, PA reported in the top panels) and of the entire Pareto approximate set (bottom panels).

Results in Figure 6a show that the best solution in terms of hydropower production (PH) is more sensitive to the inflows variability (ensemble E1) than to the evaporation rates variability (ensemble E2). However, the combined effect of inflows and evaporation rates produces a much larger variability in the mixed ensemble E3 as quantified by the larger 25th and 75th percentiles box. Similarly, the evaluation of the boxplot over the performance of the entire Pareto approximate set (Figure 6e) shows a significantly larger uncertainty in the mixed ensemble. Such sensitivity in the evaluation of the solutions over the mixed ensemble can be explained by the fact that maximizing the hydropower production in a system with multiple reservoirs, which are located both in parallel and in series, requires an accurate balance of releases and hydraulic heads against inflows and evaporation losses. The optimization of the system operations over history establishes an equilibrium over the observed hydrologic conditions, which is likely to be altered when exposed to synthetically generated drivers.

Figure 6b shows that policy PF is quite insensitive to ensembles E1 and E2 in terms of flood control, while the performance uncertainty explodes in the mixed ensemble (E3). This result is due to the unintentional spills from Masjed Soleyman reservoirs produced by the combined effect of stochastic inflows and evaporation rates, which increase the magnitude of the floods downstream of the dam. The effect appears only in the mixed ensemble for policy PF because this alternative looks only at flood control and tries to keep a large flood pool. On the contrary, the other Pareto approximate policies maintain high water levels for hydropower production and water supply and produce unintentional spills also in ensemble

E2 (Figure 6f), while the variability of the inflows in ensemble E1 is less impacting due to the location of Masjed Soleyman in series with Karoun 1 reservoir.

The analysis of the performance uncertainty in terms of water supply in Figure 6 (panels c-d-g-h) suggests different sensitivities with respect to hydropower and flood control. The best solutions in terms of water supply for the agricultural districts (PI in Figure 6c) and for Ahvaz city (PA in Figure 6d) are definitely less sensitive than the entire Pareto approximate set (Figure 6g-h) in all the three ensembles, with larger uncertainty in the case of E1 than E2. This result is probably due to the long-term dynamics of water supply operations, which are less affected by hydroclimatic uncertainties than short-term operating objectives such as hydropower or flood control. It is worth noting that the evaluation of the boxplot in terms of J^{Irr} and J^{Ahvaz} on the entire Pareto approximate set, thus including policies that balance water supply with the other objectives, shows growing performance uncertainties when transitioning from E1 to E2 and E3, ultimately confirming the key role of evaporation rates in the system under study.

Analysis of the operating policies

To better understand the behavior of the system under different operating policies and its vulnerability when simulated over synthetic inflows and evaporation, we visualize the probability density function (PDF) of the reservoirs' storage over time. These PDFs are estimated from the Monte Carlo simulation over the mixed ensemble. Figure 7 shows these estimates in log space for the policies PH (best solution in terms of hydropower production, left column) and PA (best solution in terms of water supply to Ahvaz, right column), with high probabilities shaded black, moderate probabilities dark gray, and low probabilities light gray. A red dashed line represents the storage value at which the spillways are activated.

The comparison of these two extreme policies highlights clear differences in the resulting storage dynamics. Policy PH (left column) keeps both Karoun 1 and Dez reservoirs full over the entire year to maximize the hydraulic head, which contributes to the energy production (see eq. 2). At the same time, the limited storage capacity of Masjed Soleyman suggests creating a small buffer to prevent the activation of the spillways. This strategy is more evident during the dry seasons (from April to September), while storage dynamics is more variable during the wet season.

On the contrary, Policy PA (right column) activates an evident drawdown cycle in both Karoun 1 and Dez reservoirs from June to the end of September, when the water demand of Ahwaz is high (see Figure 2). The two reservoirs are instead full during the rest of the year. Similarly to policy PH, Masjed Soleyman has a more variable behavior. However, at the beginning of the high-demand period, also Masjed Soleyman contributes to the water supply to Ahwaz and the storage goes through a short drawdown period. This is followed by three months of constant storage, during which the reservoir's release is equal to the inflow, i.e., the water released by Karoun 1.

Finally, it is worth noticing that all reservoirs under both PH and PA are exposed to high risk of spilling water when simulated over the mixed ensemble. This waste of water is due to the variability of the synthetic hydrologic conditions in the mixed ensemble, which includes years with inflows' realizations that are higher or with evaporation rates' realizations that are lower than the historical one used during the policy design. This produces an unexpected excess of water in the reservoir, consequently increasing the frequency of spillages (which are activated when the storage exceeds the red dashed line in the figure). These episodes are more frequent under policy PH, which is interested in maximizing the hydraulic head for increasing the energy production, and are particularly evident for Masjed Soleyman, which has a smaller storage capacity than Karoun 1 and Dez reservoirs.

CONCLUSIONS

The optimal operations of water reservoirs can increase water availability for different economic sectors and contribute to regional growth and development. However, increasing variability and uncertainty in the hydrologic regimes may negatively impact on existing water systems operations. This paper contributes a multi-objective assessment of the impacts of hydrologic uncertainties, partitioning the role of inflows and evaporation, on the operations of three multipurpose reservoirs in the Dez and Karoun rivers system.

Our results show that the system performance is highly sensitive to both inflows and evaporation uncertainties. In particular, though often neglected, the role of the evaporation rates' uncertainty is comparable to the one of the streamflows in such arid river basins. In addition, the combined effects of both streamflow and evaporation uncertainties produces larger impacts than when the two variables are considered independently. Finally, we show how the role of the hydrologic uncertainties vary depending on the nature of the operating objectives considered. Long-term objectives (e.g., water supply) are mainly dependent on inflows uncertainty. On the contrary, evaporation rates' uncertainty plays a more relevant role on short-term objectives (e.g., hydropower production and flood control).

A key outcome of this study is the generation of a more informative context for supporting the local water authorities and reservoirs operators in increasing the resiliency of the current operations. The uncertainty about the future hydrological conditions may produce relevant impacts on the water balance, increasing the risks of producing unintended consequences such as excessive drawdown of the reservoir storage or large spillover due to the activation of the spillways. In addition, these findings have important implications for the design of future operations of the expanded network of reservoirs, including the ones currently under construction in the upper part of the basin. These reservoirs will provide additional flexibility in terms of controlling the available water in space and time, but their coordinated management should be designed by properly characterizing the future hydrologic uncertainty. Moreover, water authorities might consider improving the existing monitoring network to obtain more reliable data for modeling streamflow and evaporation processes.

Future research efforts will focus on improving the statistical significance of the analysis by extending the historical horizon and enlarging the dimension of the stochastic ensembles. This twofold improvement will also allow exploring how decision-makers would cope with the resulting large uncertainty in the operating policies' performance. A second aspect to be improved is the possibility of linking the irrigation water demand to the underlying climate conditions, as crop requirements are significantly affected by temperature and evapotranspiration. We also plan to expand the analysis to explore the impacts of long-term non-stationary changing conditions, such as ensemble of climate projections, which are expected to provide additional insights about potential system vulnerabilities over a longer time horizon. Finally, the design of effective actions to mitigate the identified system vulnerabilities will support policy makers in prioritizing responses and adaptation strategies to the changing climate.

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List of Tables

TABLE 1. Dams' characteristics.

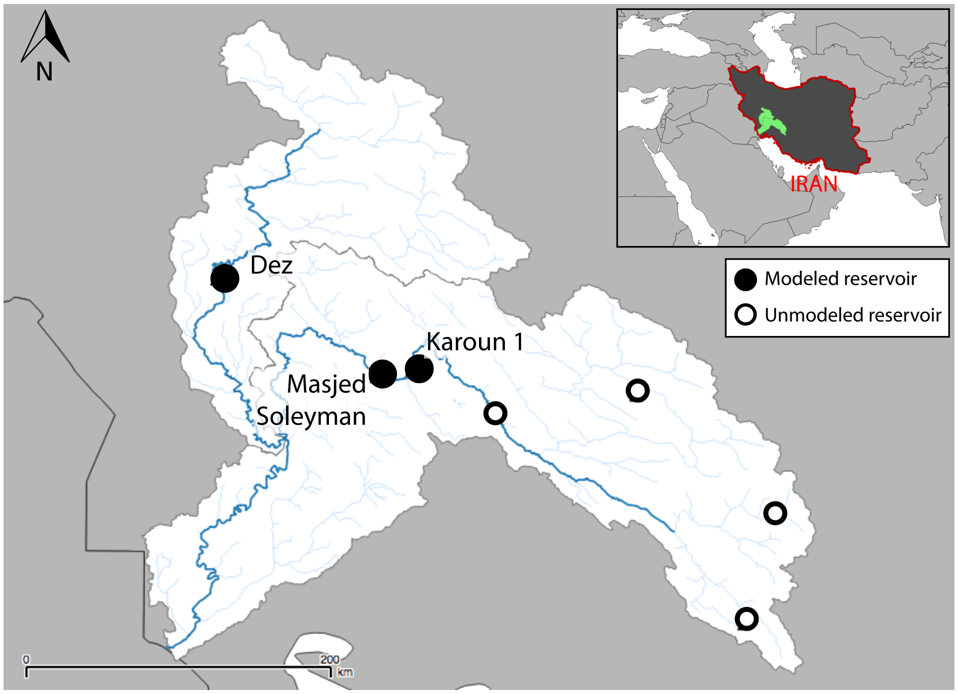
Dam	Dez	Karoun 1	Masjed Soleyman
Storage capacity (at normal level) [Mm^3]	945	824	261
Installed capacity [MW]	520	2000	2000
Number of turbines [-]	8	8	8
Turbine capacity [m^3/s]	2856	1528	1280
Turbine efficiency	0.89	0.90	0.92

TABLE 2. Annual values of evaporation [mm] reported in the literature or estimated by different models.

	Dez	Karoun 1	Masjed Soleyman
Observed (Ghorbani et al. 2009)	2051.1	1705.2	1884.82
(Hooshmand et al. 2013)	1801.0	1787.0	-
(Gorjizade et al. 2014)	3836.0	-	-
model-1 (Thornthwaite 1948)	2052.1	2957.5	2957.5
model-2 (Blaney and Criddle 1950)	2132.2	2350.5	2350.5
model-3 (Kharrufa 1985)	23.21	25.38	25.38
model-4 (McGuinness and Bordne 1972)	121.31	64.97	64.97

List of Figures

(a) Karoun and Dez river basin map



(b) Karoun and Dez river basin model

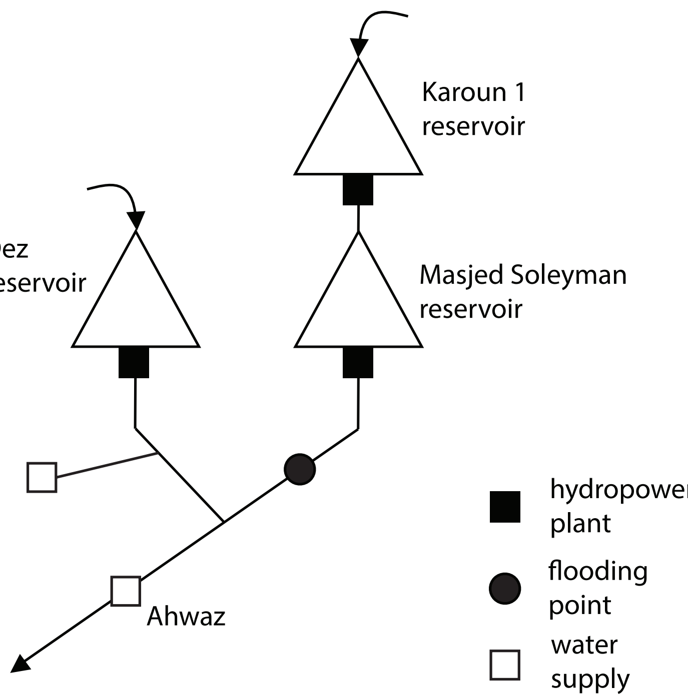


FIG. 1. Dez and Karoun rivers basin map (panel a) and schematic representation of the main model's components (panel b).

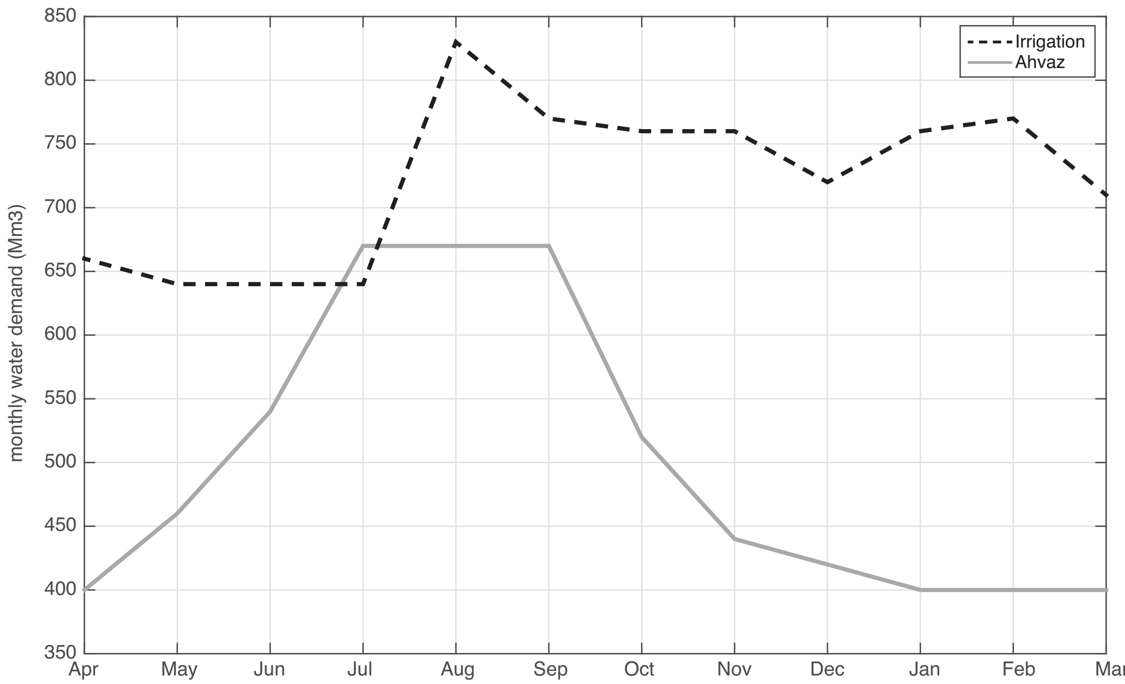


FIG. 2. Monthly water demand for irrigation in the agricultural districts downstream of Dez reservoir (dashed line) and for the water uses in Ahvaz city (solid line).

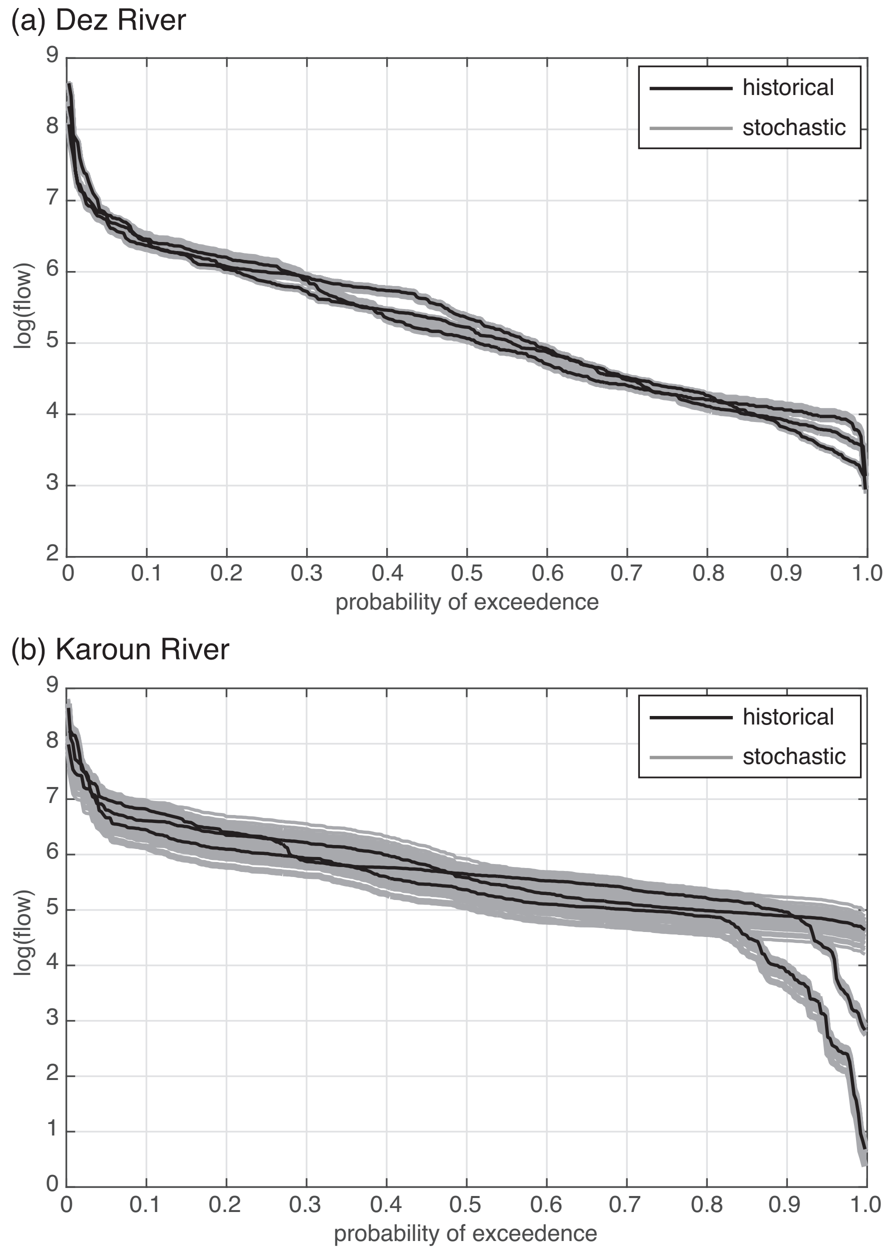


FIG. 3. Annual flow duration curves of the inflows of Dez (a) and Karoun 1 (b) reservoirs. The three historical years are represented in black, the generated stochastic ensemble in gray.

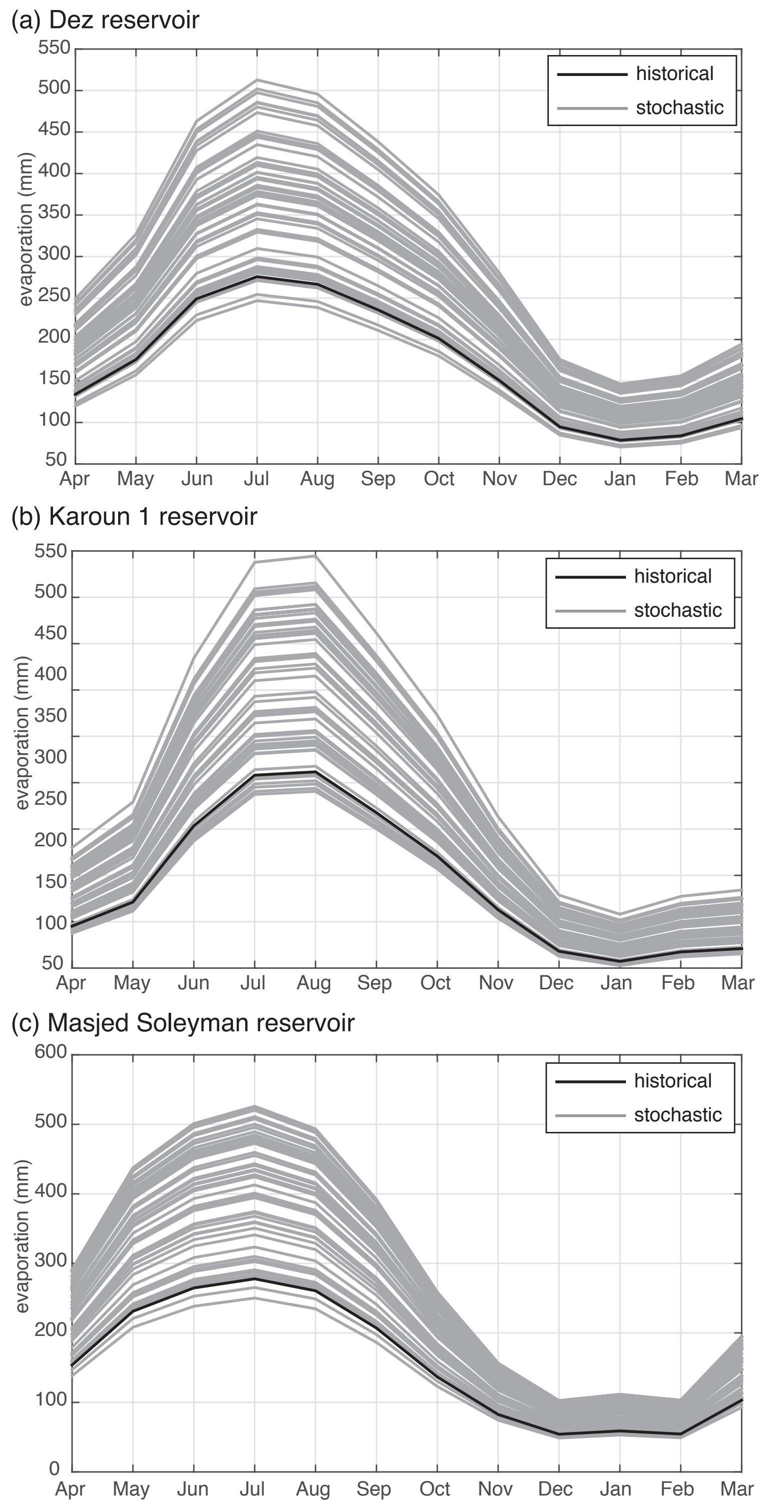


FIG. 4. Monthly evaporation rates for Dez (a), Karoun 1 (b), and Masjed Soleyman (c) reservoirs. Historical values are represented in black, the generated stochastic ensemble in gray.

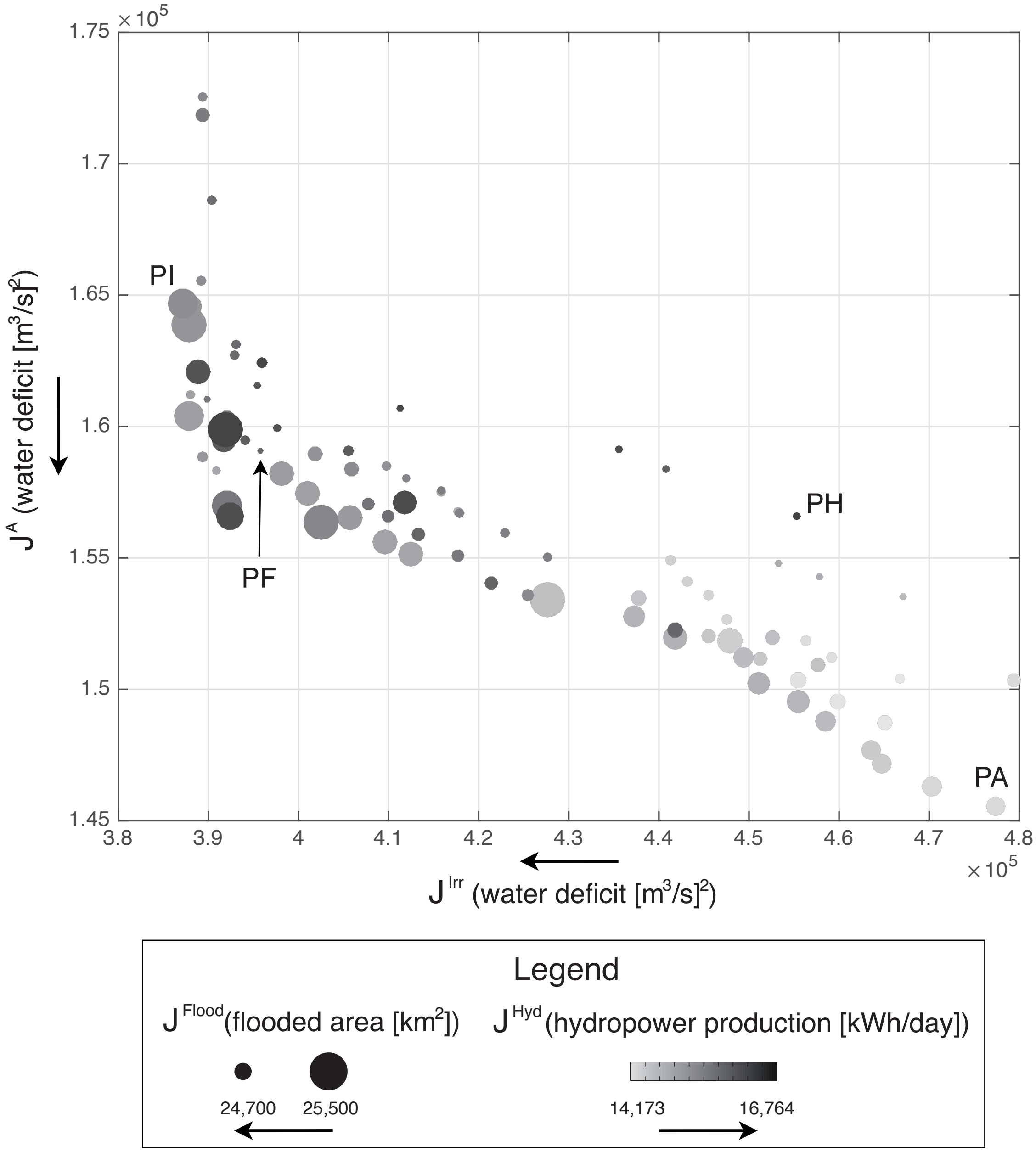


FIG. 5. Performance of the Pareto approximate operating policies evaluated over historical inflows and evaporation rates. Policies PH, PF, PI, and PA represents the best solutions in terms of hydropower production, flood control, water supply for irrigation and for Ahvaz city, respectively.

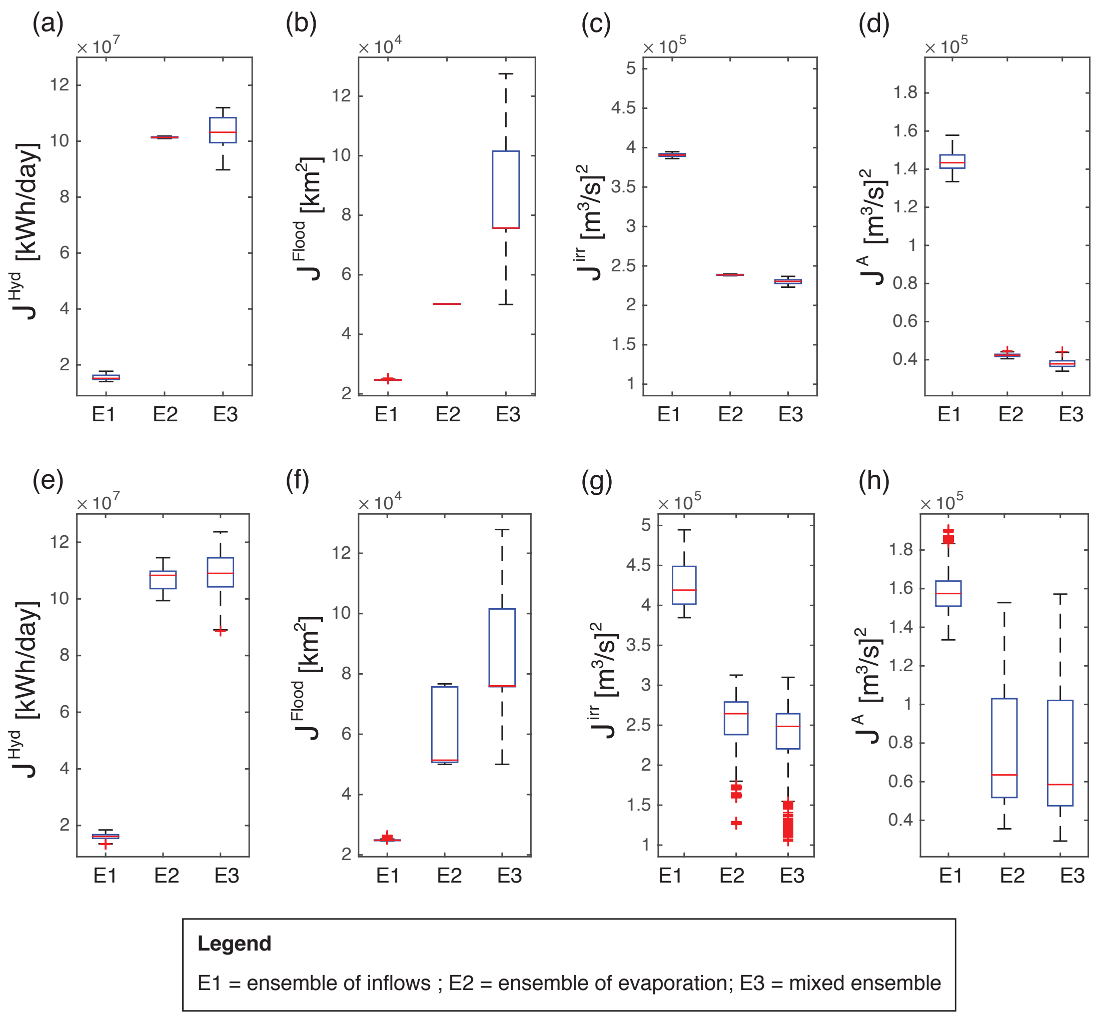


FIG. 6. Performance uncertainty over the three ensembles for the single-objective optimal solutions PH, PF, PI, and PA (panels a-b-c-d) and for the entire history-based Pareto approximate set (panels e-f-g-h).

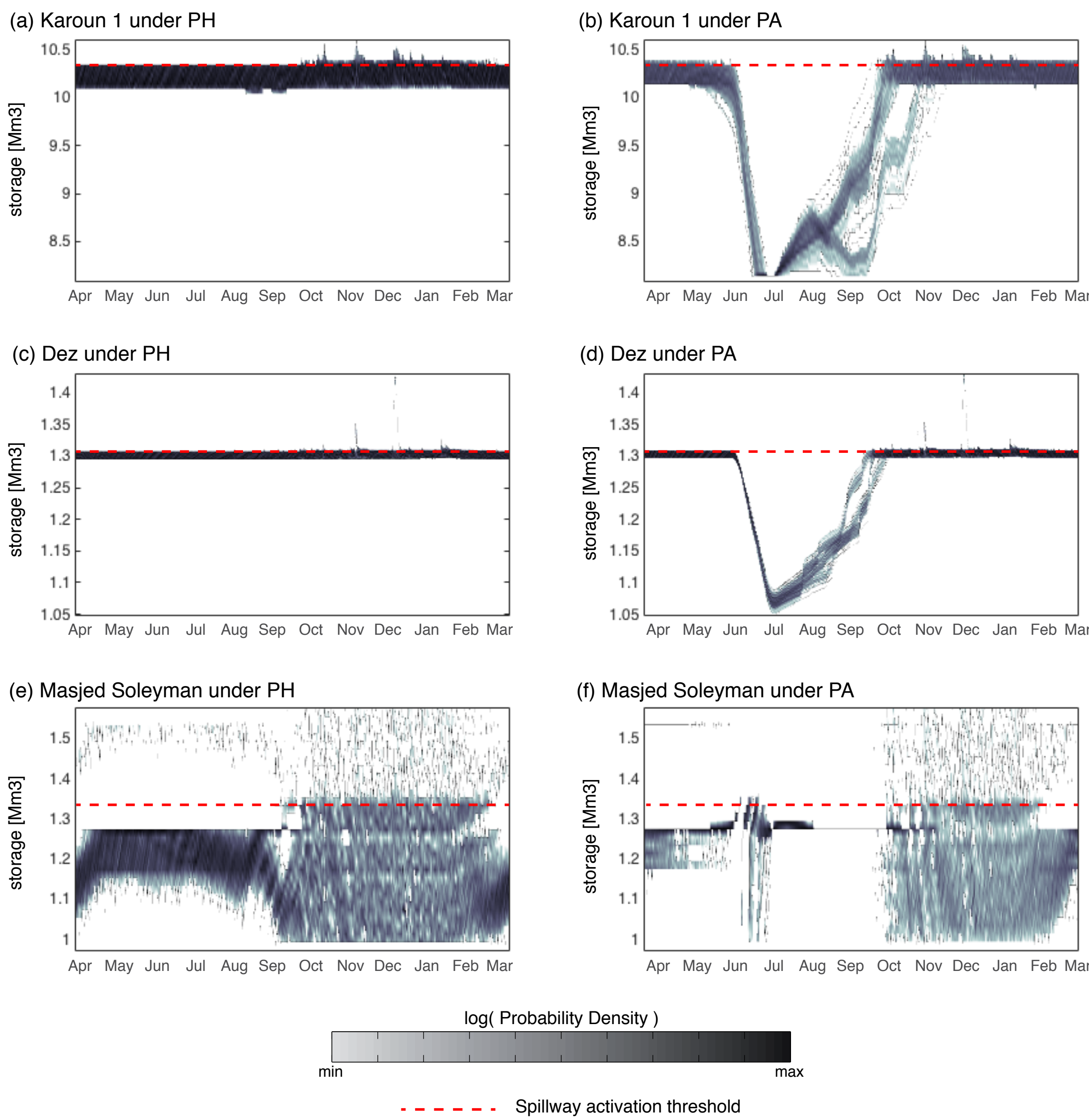


FIG. 7. Probabilistic trajectories of the storage in each reservoir under operating policies PH (best solution in terms of hydropower production, left column) and PA (best solution in terms of water supply to Ahvaz, right column). The probabilities are estimated from the Monte Carlo simulation over the mixed ensemble. A red dashed line represents the storage value at which the spillways are activated.